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A look at task-switching and multi-tasking behaviors: From the perspective of the computer usage among a large number of people

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ABSTRACT

In the past decade, online applications and working platforms, instant messengers and online social networks have become progressively mainstream with the introduction of easily accessible internet and commercially available technological devices. One of the results of the explosion of these online applications and working platforms is the emergence of more and more multitasking activity, that people are doing several types of tasks on computers or mobile devices simultaneously. In this paper, we present an intensive study on a dataset which contains over 15 million computer operation log records from 3000 random selected subjects. The dataset gives us an opportunity to look into people real-world task-switching behavior of computer usage in a very large scale. We explore the characteristics and the "star" structure of people's general task-switching and multitasking behaviors on a group level. Our experiments show the existence of Power-law distributions in subjects' task-switching activities, which suggests that most of the task-switching events in the dataset are around to a very small number of some "hub" computer-based tasks. Those top "hub" tasks include online chatting, browsing internet, document editing and online shopping. At last, the paper explored the interplay between subjects' age attribute and their active level during task-switching activities in a quantitative way.

1. Introduction

1.1. Background and related work

As the result of the increasing complexity of people's working environment and the explosion of internet based services like instant messenger, social network, etc., people are becoming less able to block out distractions from different tasks and more and more likely to switch their behaviors frequently and multitasking. These multitasking and task-switching behaviors are especially common when it comes to the scenario where people are using their computers and mobile devices (Judd & Kennedy, 2011; Kessler, 2011). For example, the notifications from emails, instant messengers or social networks constantly distract people from their current work and drive people to switching back and forth from different programs on computers or smart phones. A better understanding of how people switch their tasks on computer or mobile devices can provide a deeper insight for computer application development and design, internet advertisement industry, online education and a lot of other human computer interaction related fields.

Some recent studies have already started to investigate the tasking switching and multitasking behavior of people on a single device or between different devices (Brasel & Gips, 2011; Carrier, Cheever, Rosen, Benitez, & Chang, 2009; David, Xu, Srivastava, & Kim, 2013; Green, Sugarman, Medford, Klobusicky, & Bavelier, 2012; Ie, Haller, Langer, & Courvoisier, 2012; Judd & Kennedy, 2011; Junco, 2012; Karpinski, Kirschner, Ozer, Mellott, & Ochwo, 2013; Rosen, Mark Carrier, & Cheever, 2013; Zhong, 2013). A study by Judd and Kennedy (2011) used the log data of computer and internet usage collected from more than five hundred undergraduate medical students to study both task switching and multitasking behaviors of college students. The article written by Brasel and Gips (2011) investigated people's multi-tasking behaviors across television and Internet content through a controlled laboratory experiment, which recorded the gaze information of both younger and older individuals as they used a computer and television concurrently. Attempting to understand of the impacts that electronic communication brought to the academic learning process of people, Rosen et al. (2013) analyzed the task-switching and multitasking behaviors of students based on the observed behavior

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dataset which was collected from 263 middle school, high school and university students when they were studying in their homes.

Although the frequent task-switching and multi-tasking phenomenon attracts a lot of researchers, many researches on people's task switching behaviors suffered from the limited data sources. Some of these researches are mainly data that is from self reports or manual recordings, with very limited objective data that can provide precise task switching information. Some researchers collected data by performing controlled laboratory experiments that people are required to do some specific task-switching activities, while some other researchers captured the behavior data by direct observing people's behavior. In both cases, the behavior data they collected has the possibility to be different from what reality presents, because it is the known fact that people behave differently with other people's presence.

In this article, however, the dataset we used tracked three thousand subjects' behavior of their computer usage in real life for a month. It provides an special opportunity for us to analysis people's task-switching and multi-tasking behavior of computer usage on a large scale, and with a more objective measure.

1.2. Dataset description

The dataset used in this paper is a set of logging files that records the computer operations performed by a set of 3000 random selected volunteer subjects in China between 2014-08-01 and 2013-08-31. These subjects covers different occupations including farmer, student, freelancer, corporate manager and 10 other categories. Their ages range from around 10 to over 60.

This computer usage logs were collected by a daemon program running in the background of each subject's computer. Recorded operations and events include booting the computer, opening a new program, changing the current focused window, visiting a website and so on. For each operation record, its corresponding time information was also being tracked, which contains both the start and end time stamps. The record also contains detail information like the name of the corresponding process if any process is involved, or the URL if it is a website visiting event, etc.

Table 1 shows a snippet of the dataset. As can be seen from the table, the computer usage records in the dataset are well organized in a format with time stamp (the number of seconds after the computer booting), focused process name, process number and other detail information.

This dataset is provided by China Internet Network Information Center (CNNIC). It has 31 days observation of 3000 subjects with over 15 million computer usage records and 16,406 different processes in total. To protect the privacy of the subject, the data is anonymized.

1.3. Paper structure

The rest of this paper is organized as four sections. We first generated a mapping method which interprets the computer usage dataset as the computer-based task-switching sequence in Section 2. Based on this mapping method, we introduced the Task Switching Graph and the corresponding Power-law distribution characterization to have a general view of the structure of the task-switching behavior concealed in the dataset.

Then, in Section 3, we defined the Hub Throughput (HT) and the Multitasking Effective Hub Throughput (MEHT) to measure the importance level of different tasks on both a task-switching and multi-tasking event sequences in a quantificational way. As shown in the experiment, these two measures helped us finding the most important tasks that play very important roles in people's task-switching activities.

In Section 4, we separated 3000 subjects in the dataset into different age groups. We then introduced the Average Task Switching Rate (ATSR) and the Average Multitasking Switching Rate (AMSR). After that, we explored the relationship between people's age attribute and their task-switching behaviors using both ATSR and AMSR.

Finally, we concluded the whole article in Section 5, where we highlighted several findings and achievements of this paper and proposes several future research topics based on this article.

Table 1
Dataset snippet.

Time stamp	Process name	Process number	Extra information
...	...	...	...
261	HaiKeyUser.exe	1524	...
291	explorer.exe	772	...
589	RegGuide.exe	6040	...
...	...	...	...

2. The general view of task switching

In this section, we explored some basic properties of the task-switching behaviors concealed in the dataset we introduces in Section 1.2. We first developed a mapping that interprets dataset into a switching sequence of computer-based tasks. The Task Switching Graph was then introduced to give an bird's eye view on the task-switching structure of the dataset. After that, we detected and characterized the Power-law distributions in the Task Switching Graph.

2.1. Interpretation of the data

As described in Section 1.2, the dataset contains subjects' computer usage records during the one month observation period. Even though the log record of current focused process itself is not a direct representation of the corresponding subject's activity, it does reflect a computer-based task that the subject was doing. This can be seen from Fig. 1, which shows our assumption about the relationship between log records in the dataset and subjects' activities of computer usage. In Fig. 1, the collected log data can be considered as an time indexed triad $\{\Delta_{t_1}, \Delta_{t_2}, \ldots, \Delta_{t_k}, \ldots\}$, where $\Delta_k = (T_{t_k}, P_{t_k}, L_{t_k})$ is the triad at time t_k : T_{t_k} is the task that the person is involved at that time, like browsing the internet, composing an email and so on; P_{t_k} is the current focused process at time t_k, like Chrome, Explorer or Microsoft Word; L_{t_k} is the log item recorded in the dataset, which includes the name of the focused process P_{t_k} and some detail information about the process like the time stamp, the process number and so on.

Using the above assumption, the log data $\{L_{t_1}, L_{t_2}, \ldots, L_{t_k}, \ldots\}$ we have can be traced down to subject's computer based task switching sequence $\{T_{t_1}, T_{t_2}, \ldots, T_{t_k}, \ldots\}$ through the $T_{t_k} \to P_{t_k} \to L_{t_k}$ link shown in Fig. 1. For example, a current focused internet explorer program in the log data can be interpreted as that a person is visiting websites at that time; a log record of a focused instant

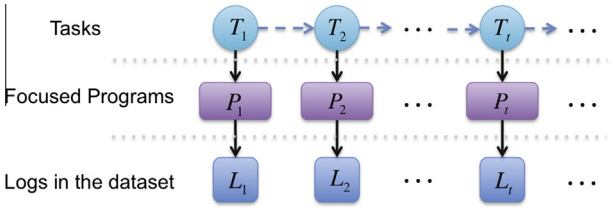

Fig. 1. Interpretation of the data.